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Two Different Approaches for NGOSS Process Modeling and Simulation

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***Abstract*—Modeling and simulation of the business processes is an important task which helps make decisions for process adjustments and improvements. This article describes and compares two different approaches for business process modeling and simulation in the field of telecommunications. In this particular case we focus on the modeling and simulation of the NGOSS Change Management process of one of the major Czech service providers in telecommunications.**

***Index Terms*—process modeling, process simulation, NGOSS process, Change Management process**

I. Introduction

The Change Management process (CMP) is still more important due to frequent changes in provided products and services. It becomes a vital part of any process portfolio of a service provider to stay competitive in the dynamic market [1]. The CMP, as any other process, can be described as a single machine. It is described by several parameters. The first is specific time distribution between arrivals of the Requests for Change (RFC). Then usually follows the buffer where are stored RFC which can't be processed due to the occupation of the necessary resources. The buffer can have different queue processing techniques which can prioritize different classes of RFCs and improves the efficiency of the whole process [2]. The processing of the RFC itself by the single machine can be described as distribution of the time that is necessary to process of the RFC. Different classes of RFC needs different amount of resources and different time to come to output of the single machine. The single machine can be illustrated as shows figure 1.

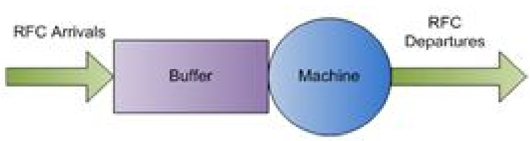

Figure 1. Single machine [3]

To be able to better monitor, measure and manage the CMP as well as to make more precise model for simulation of the CMP we modeled the process as a row of the single machines where each single machine represents one process step. Each process step ends by the defined milestone where we measured amount of time it takes to process the RFC and the amount of used resources. The milestones weren't placed randomly but their position results from the common Change Management meta-model [2] which was adjusted to conditions of the modeled process. Final model of the CMP is on the figure 2. The process steps colored by purple are external and they cannot be influenced by any change in the CMP.

II. Process simulation

There exist two basic concepts of process simulation – static and dynamic. The static models are based on the analysis of historical time series of gathered data. Statistical methods assume that gathered data ware generated by relatively stable structure (function) and extrapolated data are suitable for this function as well. Main drawback of the static simulation is its dependency on stability of the modeled process. In case there are some changes in the process, the results from the static simulation aren't relevant [4]. By using the dynamic simulation one develops an accurate simulation model which describes the behavior of a real process. The model includes the entity and resource perspectives. Performing the simulation experiments on the described model helps us to better understand the effects of running that process. In general, dynamic simulation of a real business process consists of three basic parts [5]:

- basic model building blocks (resources, activities, entities, connectors),
- activity modeling constructs (assemble, batch, branch, split and join).
- advanced modeling functions (attributes, expressions, schedules, interruptions, distributions).

Dynamic simulation is used as an appropriate means for business process modeling due to its ability to perform:

- quantitative modeling (e.g., cost-beneût analysis and feasibility of alternative designs),
- stochastic modeling (e.g., external factors and sensitivity analysis).

We have chosen the dynamic simulation of the business process not only because it is an invaluable tool for assessing the efficiency of the current process and evaluation of changes in the process but it is involved in many management methods (e.g. Six Sigma[6]). We found out following relationship between dynamic simulation and the management methods:

1. dynamic simulation is a tool for analysis of the business processes which is appropriate for majority of the management concepts and methods.
2. The dynamic simulation is one of the management methods itself. The dynamic simulation and other management methods evolve independently and influence each other. The dynamic simulation can be on the other hand used as an analytical tool in other management methods.
3. The dynamic simulation (and other quantitative methods) is source of relevant information for any of management methods. From this point of view the dynamic simulation is the core of different management methods.

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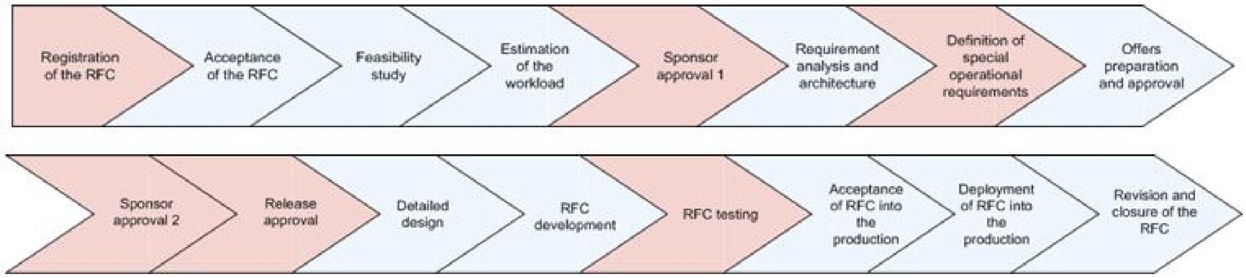

Figure 2. Change Management process model

III. Measurement of the process

The CMP was monitored and measurer for more than two years. During this time there arrived over three thousands of the RFCs. 93% of the RFCs were processes (passed the process step Registration of the RFC) and 47% of them were implemented (passed all steps in the process). For each process step we measured three key performance indicators (KPI):

- time needed for processing of each RFC,
- resources utilization,
- number of processed and rejected RFCs.

Finally we had the array for the random time values, amount of the used resources and the ration of RFCs which passed/ don't passed the process step. In this article we focus on the first KPI (time necessary for the RFC processing) and analyze the impact of the change of the time distribution on the whole process. For the evaluation of a time probability distribution for each process step we used three "goodness of fit" tests. These tests compare a random sample of data with a theoretical probability distribution function. In other words, these tests show how well the distribution we selected fits to selected data [7]. These tests are described in following paragraphs.

A. Kolmogorov–Smirnov test

The Kolmogorov-Smirnov test is used to decide if a sample comes from a population with a specific distribution. For a random variable X and a sample {x1, x2, ..., xn} the empirical distribution function X is defined as [8]:

$$F_X(x) = \frac{1}{n}\sum_{i=1}^{n} I(x_i \le x) \tag{1}$$

where I (condition) is the indicator function, i.e., 1 if the condition is true and otherwise 0. The Kolmogorov-Smirnov test statistic is defined as:

$$D_n = \sup_x \left| F_x(x) - F(x) \right| \tag{2}$$

where sup is the supremum of the set and F(x) is the theoretical cumulative distribution of the distribution being tested which must be a continuous distribution and it must be fully specified (location, scale, and shape parameters cannot be estimated from the data).

B. Anderson-Darling test

The Anderson–Darling test uses the fact that, when given a hypothesized underlying distribution and assuming the data does arise from this distribution, the data can be transformed to a uniform distribution. The transformed sample data can be then tested for uniformity with a distance test. The Anderson-Darling statistic (A2) is defined as [8]:

$$A^2 = -n - \frac{1}{n}\sum_{i=1}^{n} (2i-1)\cdot[\ln F(X_i) + \ln(1 - F(X_{n-i+1}))] \tag{3}$$

The hypothesis regarding the probability distribution is rejected in case that test statistic (A2) is greater than the critical value obtained from a table.

C. Chi-Squared test

For the chi-square goodness-of-fit computation, the data are divided into k bins and the test statistic is defined as [8]:

$$\chi^2 = \sum_{i=1}^{k} (O_i - E_i)^2 / E_i \tag{4}$$

where Oi is the observed frequency for bin i and Ei is the expected frequency for bin i. The expected frequency is calculated by:

$$E_i = N(F(Y_u) - F(Y_l)) \tag{5}$$

where F is the cumulative distribution function for the distribution being tested. Yu is the upper limit for class i, Yl is the lower limit for class i and N is the sample size. This test is sensitive to the choice of the bins. There is no optimal choice for the bin width [7]. The best choices should produce similar but not identical results. All three tests were used in both modeling and simulation approaches. For the assessment of the best probability distributions we used two different software: EasyFit and the Input Analyzer of ARENA from Rockwell Automation. The EasyFit is more appropriate for distribution fitting in this case but it uses distributions which ARENA can't simulate so we used both of these tools.

IV. Values evaluation results for first approach

The measured random time values were compared with almost fifty distributions from Normal, Students or Longnormal to Beta or Erlang. The distribution fitting was supported by the distribution fitting software EasyFit and Input Analyzer of ARENA. The fitting was done for all process steps illustrated on the figure 2. Table I contains the distributions which fitted the best for these sets of random values. There are different probability distributions listed in the left column and the different fitting tests which were used

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with their rankings in the upper row of the table. Table is sorted by the ranking from Kolmogorov–Smirnov test. The resulst are taken from EasyFit.

TABLE I
DISTRIBUTION FITTING FOR "FEASIBILITY STUDY" ACTIVITY

Distribution	Kolmogorov - Smirnov		Anderson - Darling		Chi-Squared	
	Statistic	Rank	Statistic	Rank	Statistic	Rank
Pareto 2	0.18619	1	139.32	3	546.82	5
Beta	0.19196	2	141.82	4	524.03	4
Wakeby	0.20681	3	119.4	1	416.1	2
Log-Logistic	0.20681	4	119.4	2	416.1	3
Phased Bi-Exponential	0.27583	5	571.26	15	1946.4	24

As you can on the example there are listed Pareto 2, Log-Logistic and Beta. They are very highly ranked not only illustrated process step but for all other process steps as well. All process steps have similar distribution in time. From our experiment results that we can built the CMP process model and simulate it as a row of process steps where is used only one of the following three distributions:

- Pareto 2,
- Log-Logistic,
- Beta.

On the figure 3 you can see graph of time distribution of Feasibility study process step described by Beta distribution. As a result we can make a model of CMP easily by using only one of the three above mentioned distribution function.

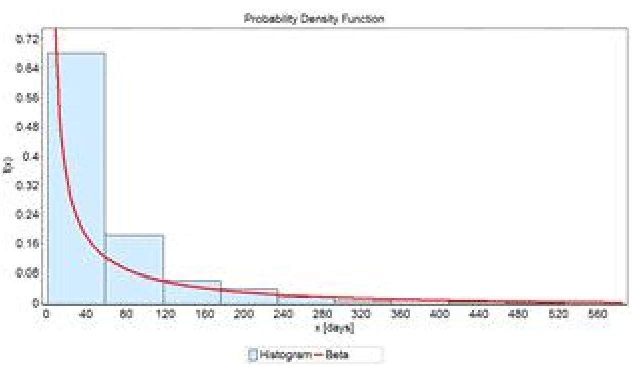

Figure 3. Time distribution of the Feasibility study activity by Beta distribution 0.999 + 583 * BETA(0.371, 3.23)

V. VALUES EVALUATION RESULTS FOR SECOND APPROACH

Although the simulation model of the CMP based on above results is reliable and accurate it doesn't meet all requirements which arose during the simulation of various scenarios and changes in the process. As we simulated different impacts of the changes on the model we found out that any change we made in process have very low impact on the RFCs which are processed for certain amount of time. Based on this finding we defined lower and upper time limit. In case that the RFC is processed longer than upper time limit or shorter than the lower time limit there is almost undetectable effect on the processing time by introducing a change into the CMP. The impact of changes can be satisfactorily quantified (changes of processing time or resource utilization in the process) only for RFCs whose processing time is between defined time limits.

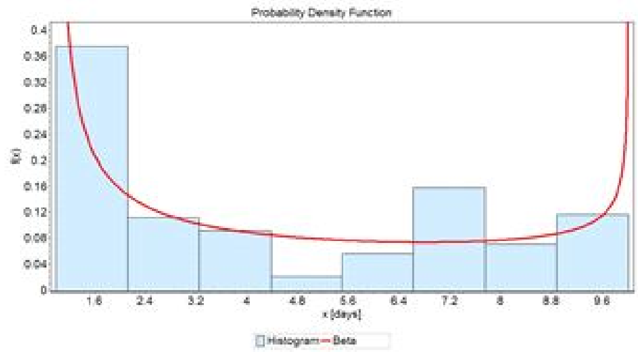

Figure. 4. Time distribution of the Feasibility study activity for FRCs
shorter than 11 days by Beta distribution 0.5 +
10 * BETA(0.615, 0.974)\

The lower time limit can be moved by shortening of the measurement unit which was set to one day in this case. The higher boundary can't be affected by any change introduced to the model. It is caused due to the fact that all RFCs which stayed in process for very long period of time were delayed in external process steps (process steps filled with white color in the figure 2). For this reason we set two time limits – 10 days for lower time limit and 115 for upper time limit – and made a model where there are three different subclasses of RFCs which differs in time of processing. Subclasses are defined by the time the RFC needs to be fully processes in comparison to the introduced time limits.

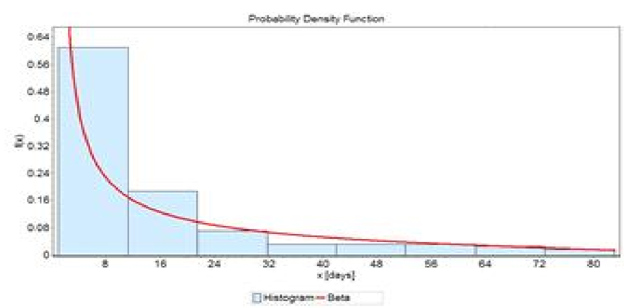

Figure. 5. Time distribution of the Feasibility study activity for FRCs longer than 10 and shorter then 115 days by Beta distribution 0.5 + 10 * BETA(0.615, 0.974)

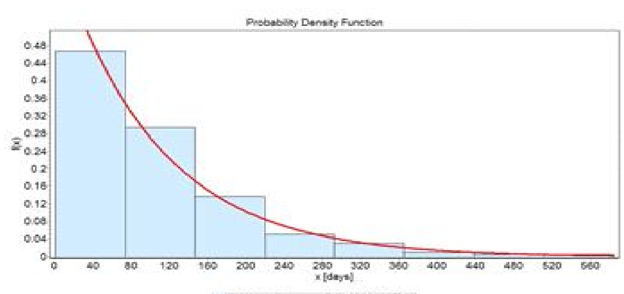

Figure. 6. Time distribution of the Feasibility study activity for FRCs longer than 115 days by Exponencial distribution 0.999 EXPO(81.5).

The probability fitting was done in the same way as in the first approach. The major difference is that there is no similarity in the any of subclass of the RFC as in the previous method so we had to use full set of probabilities to model the process. On the figures 4, 5 and 6 can be see the best fit probability for the process step Feasibility study lasting till 10 days, from 11 till 115 days and more than 116 days respectively.

VI. Conclusion and future work

The paper introduces two different approaches for the business process modeling and simulation. Both approaches were tested by the modeling and simulation of the NGOSS Change Management process of the one of the major telecommunication service providers. In the first case the model of the presented process was described as a row of the activities. We found out that all process steps have a similar time distribution. This helps us to build a much simpler model which can be based on one of above proposed probability distributions and implement changes of the process in fast and efficient way. Evaluation of these results will continue with comparison of the differences which are caused by usage of one, two or three of proposed distribution against the complex model which doesn't follow our results. There will be measured and modeled the Change Management processes of another telecommunication service provider to approve and generalize our results. In the second case we used another approach. It helped us to focus on the area of the process which is affected by changes introduced into the process. It is more precise for monitoring the impact of the changes but is much complicated for the modeling and simulating. The suitability of this approach will be further studied on the different business process within ICT service providers.

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